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Memo

To: Andie Biggs
Office of Energy Infrastructure Safety

From: Gregg Morris and Zoë Harrold

Informal Comments of the Green Power Institute on the Wildfire Risk Modeling Working Group

Green Power Institute (GPI) representatives joined the Risk Modeling Working Group in July 2022 and attended the July 13 and August 10, 2022 meetings. These meetings covered the topics of Modeling Algorithms, Components, Linkages, Interdependencies, and Climate Change. We provide the following comments in response to the August 17, 2022 email from Andie Biggs, OEIS, seeking comments on lessons learned, future modeling improvements, and meeting topics.

Our comments generally address topics and recommendations from the perspective of how modelling methods and reporting effect applications for wildfire mitigation planning and implementation.

We include the following lessons learned that correlate to recommendations for future areas of improvement:

- *Establish a wildfire risk mitigation planning target, for example a 1-in-10-year wildfire risk event planning threshold, or other metric that can guide wildfire risk planning models.*
- *Machine learning PoI planning models may result in biased outputs. An assessment of result bias is warranted to address the potential for risk mitigation blind spots.*
- *Evaluate existing and alternative consequence quantification approaches and whether longer fire spread simulations are necessary.*

- *Ingress and egress risk evaluation methods may overlook important factors limiting evacuation rate.*
- *Flattened risk scores mask the overlap of risk from multiple risk drivers such as layered lower (e.g. CFO-animal) and higher (e.g. CFO-vegetation) frequency risk drivers. This removal of information presents challenges for assessing how modeling methods influence granular risk scores and inform risk mitigation.*
- *Utilities are in the process of determining risk model uncertainty at the individual variable level, though progress at each utility is not transparent.*

1. Any key lessons learned from previous meetings, including identification of meeting topic area (attached is the schedule of topics for reference), as applicable

1.1 Establish a wildfire risk mitigation planning target, for example a 1-in-10-year wildfire risk event planning threshold, or other metric that can guide wildfire risk planning models.

The August 10, 2022, discussion raised important issues regarding wildfire risk modeling and the methods and assumptions applied for driver specific PoI and Consequence metrics. We appreciate comments from J. Mitchell, S. Savage, and the utility modelers, which drove the discussion. The following assumptions in wildfire risk planning models came under scrutiny:

a) Averaging the wildfire consequence at each asset node (i.e. the MAVF transformation of Technosylva wildfire spread models) for all simulations run, versus other method(s) (e.g. median, kernel density estimation).

b) Whether PoI risk drivers are, and should be, treated as independent versus dependent variables relative to the wildfire consequence they are multiplied by.

These assumptions lead back to a foundational question mentioned during the meeting – what level of wildfire risk should the grid be designed for? That is, what planning standard will guide wildfire risk modeling and therefore risk mitigation planning and implementation. GPI believes this question is foundational to guiding the next phase of wildfire mitigation planning, including with respect to (a) and (b) following.

a) Wildfire Consequence: Granular ignition consequence constitutes a Poisson distribution of independent, MAVF derived consequence values determined based on each of many (n) fire spread simulations performed at the location of each asset. The IOUs are averaging these MAVF-based wildfire consequence values to arrive at a single consequence value at the location of each utility asset. Concern was raised regarding whether averaging was appropriate. Averaging assumes that the observations have a normal distribution and may not be suitable for skewed distributions, where using the median is more appropriate for summarizing the most probable outcome. It also eliminates information on the distribution tails, especially since the IOUs are not providing any summary statistics on skewness or distribution. Averaging also assumes that fire spread consequence distributions are unimodal versus multi-modal (e.g. versus bi-modal) at each asset. Based on available data it is not clear whether granular wildfire spread model-based and MAVF converted consequence values have approximately normal, skewed, or multi-model distributions or what the width of the distributions are. As such it is possible that using the average is not the optimal representation of consequence at each asset.

Liberty uses a kernel density estimation for wildfire consequence at each asset. The degree of smoothing is unknown, as well as whether and how they convert the smoothed distribution into a single granular consequence value and resultant risk score. GPI has previously raised concerns that Liberty appears to perform a variable number of wildfire simulations (n) at each asset location, which may raise issues in terms of comparability between locations (GPI comments on 2022 SMJU Draft WMPs, June 20, 2022).

The IOU's intention to account for model uncertainty by running many wildfire spread simulations based on a defined set of worst weather days and averaging the resultant consequences appears to be generally well intentioned and on track. However, it is also true that the way in which a singular consequence value is determined at each asset from the distribution of wildfire spread simulation outputs is important both in terms of mathematical appropriateness as well as for risk mitigation implications. For example, taking the average of a skewed consequence profile may overestimate or underestimate consequence depending on whether it is right of left skewed; a possibility since wildfire spread simulations are stopped at 8 hours and can have zero spread.

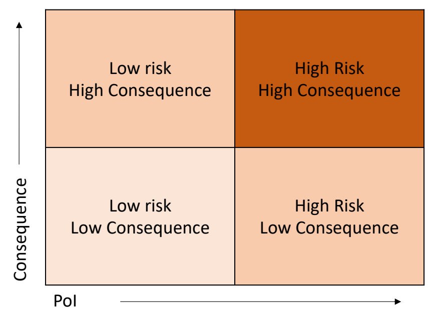
Establishing a best practice for how or even if a consequence distribution should be converted into a single consequence value is important for estimating granular risk. More importantly the selected method can affect the wildfire mitigation planning standard. For example, taking the average, median, or 95th percentile consequence score will result in very different risk scores at each asset, and could potentially result in very different risk maps. From a planning and application standpoint, the definition of a planning standard is therefore important for guiding how consequence and overall risk is mathematically defined.

Depending on the risk mitigation/planning threshold, the average or even median consequence risk may not be the optimal consequence value. If the planning threshold is for a 1-in-10-year wildfire consequence, or some other definition such as the mere possibility of a catastrophic wildfire whether in a 10 year or 100 year timeframe, then it may be more appropriate to utilize alternative consequence values (e.g. max, percentile, etc.) and/or a range of values to define confidence intervals. Alternatively, is it necessary to avoid condensing consequence probability curves into a single value altogether and instead use the consequence distribution in a Monte Carlo simulation? This discussion also begs the question of how accurate and precise the final risk value needs to be and the trade-offs in terms of strategic and timely risk mapping and mitigation, computational power and feasibility, or other factors.

b) Risk driver PoI and consequence as independent versus dependent variables – The IOU planning models assume that PoI risk and consequence are independent variables. This effectively quantifies "maximum" possible risk for a given ignition in a specific location, regardless of driver and in the absence of quantitative correlations between ignition drivers and specific weather patterns (e.g. FPI). This approach, while perhaps not capturing an accurate snapshot of risk at the present time, does function to avoid potential underestimation of risk by quantifying something that approximates maximum potential risk. That is, utilities are treating all risk events as though they are low or high

PoI risk x high ignition consequence (i.e. Figure 1 below, top row), versus accurately modeling the dependence of ignitions from each risk driver with the most likely wildfire consequence of that ignition (Figure 1).

Figure 1 Generalized schematic of PoI and consequence dependencies



Comments by J. Miller and S. Savage raise concerns that the current approach overestimates wildfire risk from drivers such as contact from object (CFO) - animal ignitions and other ignition drivers that may not be linked to/caused by high-risk wildfire conditions (i.e. are independent); and that this over-estimation dilutes higher-risk PoI drivers such as line-slap, and CFO-vegetation risk that are linked to windy and high risk FPI conditions, such that PoI and consequence are dependent variables. Mitchell's analysis suggests that pooled ignition and wildfire data across the state allowed for a more statistically robust assessment of the evolution of an ignition into a major or catastrophic wildfire associated with each ignition risk driver. Results showed significance for wind-linked risk drivers causing catastrophic wildfires. However, he notes that these analyses are still limited by small datasets.

The core issue is whether PoI and consequence should be treated as independent or dependent variables, or put another way if models should make a determination that are risk drivers and consequence are linked by correlation versus causation. There is, however, nuance in this assessment. For example, the issue was raised that CFO-animal drivers may be decoupled from high-risk FPI conditions, but that this does not mean that CFO-animal caused ignitions cannot or will not occur concurrent with high risk FPI conditions. Utility representatives also stated that PoI drivers such as line slap can happen under a range of conditions, not just high FPI conditions. Liberty stated that their risk models couple PoI risk drivers with FPI conditions as dependent variables. However, they are simply not modeling risk from drivers such as CFO-animals and other ignition drivers that are considered independent of their wildfire spread simulation conditions. Leaving out ignition risk drivers is a questionable practice, and it should be taken into consideration in interpreting the results.

It is also important to note the limitations of utilities' machine learning PoI risk models. Utilities stated that covariate selection is not designed to eliminate model bias or even determine "truth" in terms of underlying risk drivers (e.g. root cause analysis), but rather it is developed to maximize granular ignition predictive power based on training and test data subsets. Based on some insights into the model covariates these ML models have many "levers" that include everything from equipment age to power flow conditions/ pulses, as well as local weather and climate patters (e.g. wind). The important point here is that it is not entirely clear whether there are sufficient studies/insights at this time to quantify the degree of PoI and consequence dependence for all risk drivers, and whether some risk drivers occur entirely independent or dependent of high-risk wildfire conditions.

GPI appreciates all comments from the utilities and stakeholders during the August 10, 2022, Risk Modeling Working Group meeting and finds merit in all of the concerns regarding data adequacy and modeling approach. We add that these considerations all raise the root question of whether risk modeling can or even should reflect precise current day risk versus maximum possible risk, or if they should be calibrated to another risk planning threshold entirely.

<u>Current Risk Planning Threshold</u> – A wildfire risk mitigation planning vision was established by the Wildfire Safety Division (WSD) in the Utility Wildfire Mitigation Strategy and Roadmap for the Wildfire Safety Division (WSD Roadmap, 2020). The WSD vision states:

> The proposed activities in this report provide the foundation to achieve a new long-term vision for the WSD and the utility sector:

> *A sustainable California, with no catastrophic utility- related wildfires, that has access to safe, affordable, and reliable electricity.*
>
> This is a bold and aspirational vision, that is used for the purposes of this strategy and not meant at this time to be used to enforce penalties or interpret statute, but rather to give the WSD and utilities something to strive towards together and to set a high bar for the WSD and utilities to re-imagine a different future for California….
>
> For the purpose of this strategy only, "catastrophic" refers to any fire in California that meets one or more of following criteria, which are derived from California's historic deadly and destructive fires. The criteria are:
>
> **Public Safety** Directly causes one or more deaths
> **Property** Damages or destroys over 500 structures
> **Natural Resources** Burns over 140,000 acres of land (WSD Roadmap, 2020)

Notably the WSD 2020 Roadmap specifically refers to this planning benchmark as a vision and that it is not to be used to enforce penalties or interpret statute. As the intended target for utilities to strive for, one could argue that the current risk models are aligning to this vision by assuming an approximation of maximum consequence risk for all potential ignitions regardless of ignition driver. That is, utility models are currently designed to include lower frequency, or less probable, catastrophic wildfire risk drivers.

There is a hierarchical planning gap that includes the lack of an established, top-down risk planning expectation other than what is in the WSD high-level vision. This gap is reflected in risk modeling methods, and closing this gap begins with establishing a risk mitigation planning target. An example of an energy sector risk mitigation planning target is the Resource Adequacy Planning Reserve Margin (RA PRM). The CPUC established a 1-in-10-year outage event risk mitigation target and calibrated the RA PRM to this target – meaning the 15 percent RA PRM is expected to provide sufficient capacity to prevent outages until and unless a greater than 1-in-10-year event occurs, under which conditions widespread outages of a defined extent and duration would be expected to occur.

Applying this concept to wildfire mitigation planning opens many questions: Should risk modeling guide mitigations that address a 1-in-10-year catastrophic wildfire event, a 1-in-100-year event? If so, does that threshold include, for example, CFO-animal ignitions coincident with high FPI conditions. What would the intended and unintended outcomes be of weighting wildfire consequence values that are multiplied by potentially independent PoI drivers, and what threshold of risk planning would this establish for wildfire mitigation at each utility? How is it standardized? Is there adequate data to determine PoI and consequence dependence, event probability, or overall risk scores at a high level of precision? What can we learn from existing electric sector risk planning metrics, established by the CPUC and implemented by the utilities, that can inform wildfire risk planning targets.

It remains the case that wildfire mitigation is expensive and that wildfire mitigations take time to implement. The purpose of the risk mitigation models is to inform strategic and granular mitigations that reduce costs and target the highest risk locations first in support of more rapid risk buydown. Establishing one or multiple risk planning targets could guide risk model design that will in turn affect mitigation selection. For example, a target of modeling, planning for, and mitigating a 1-in-100-year catastrophic wildfire event would warrant multiplying low frequency PoI events with lower probability, higher wildfire consequence outcomes. The outcome of such a model may include more expansive "high-priority" risk areas and/or alter the risk score range across a utilities' territory. While at the other end of the planning spectrum a 1-in-2-year wildfire planning target might focus risk modeling on more frequent PoI drivers and average consequence values. Given the current need for substantive mitigations across much of the HFTD, it may even be prudent to establish multiple planning targets that guide phased near-, mid-, and long-term mitigations based in high-, medium-, and lower-probability wildfire risk. Establishing risk planning metrics can also help align risk models and modeling approaches across utilities.

A risk planning target will also guide RSE and mitigation valuation by way of risk modeling outputs. For example, the RA PRM effectively establishes that the benefits of planning for a 1-in-10-year outage event is worth the cost of the resultant 15 percent over-procurement requirement. In the wildfire risk planning context, a 1-in-100-year catastrophic wildfire risk planning target and resultant model output might affect RSE scores across large swaths of the HFTD that quantitatively justify undergrounding over covered conductor.

While GPI does not advocate for a specific wildfire risk planning target at this time, or even the form of that target (e.g. a 1-in-n-year event, consequence threshold, etc), we do recommend that the final RMWG report advocate that the OEIS or CPUC establish a quantitative risk planning target through a process that includes ample opportunity for stakeholder comment. It may be prudent to address this in a working group meeting to discuss possible options for a quantitative risk planning target. Defining this planning target will in turn guide risk modeling and risk mitigations – similar to how a standard reliability requirement and metric is used to assess the adequacy of systemwide resource portfolio modeling and determine the RA PRM of 15 percent.

1.2 *Machine learning PoI planning models may result in biased outputs. An assessment of result bias is warranted to mitigate the potential for risk mitigation blind spots.*

All models have errors, so it is to be expected that utilities ML PoI risk planning models are not entirely accurate when it comes to predicting where and what caused known ignitions in the test data set (30 percent), after the model is developed using the training data subset (70 percent). In the July 13, 2022, meeting the utilities reported that the model development process used approaches: (i) to intentionally introduce bias, (ii) that could unintentionally create bias, and (iii) to reduce bias. They further noted that some approaches used to "create better models that may introduce bias" include optimization to increase model predictive capabilities and that these approaches are not intended to determine "truth." GPI sees no specific issue with these potential model bias factors, but rather raises the concern that unchecked, unintentional bias in the output predictions could produce model blind spots or other biases that could influence risk mitigation planning and implementation.

In the October 5-6, 2021, risk modeling workshop GPI suggested that the Utilities develop and provide an assessment of ignition prediction bias, including ignitions that are not predicted by the PoI ML models (i.e. planning models). To date it does not appear that the utilities using machine learning models have a process to periodically assess whether the output predictions are biased, what those biases are, how they might mitigate them, or minimally how they will account for the bias in the process of implementing risk-informed mitigation plans. Utilities' modelling methods and documentation should include an assessment of what ML model biases might look like and establish a process for periodic bias assessment that documents known biases. This process should be iterative to continuously build an understanding of what ML derived PoI risk bias can and does constitute, how it changes with each model version, and how model bias should be taken into account in risk-informed mitigation decision making.

Notably, the focus on predictive power versus "truth" should also remind us that the ML models may not provide optimal insights into risk driver thresholds or causes. For example, maximum operating wind speeds for different conductor types, the age threshold at which point an asset should be preemptively replaced to mitigate risk, or why a given area is particularly prone to CFO-animals. While the predictive power of PoI ML models based on variable selection may facilitate cause and effect studies, the bias in these models may not accurately inform root causes of ignitions. The utilities should continue to study and identify ignition risk factors and root causes on their systems, seperate from ML modelling.

1.3 Evaluate existing and alternative consequence quantification approaches and whether longer fire spread simulations are necessary.

An issue raised by MGRA in their comments on the 2021 WMPs is that the 8 hour wildfire spread simulations may underestimate wildfire risk in more remote areas where ignitions can lead to large and even catastrophic wildfires that traverse substantial distances and can ultimately encroach on WUIs that are not proximal to the point of ignition. Discussions regarding the duration of wildfire spread simulations are reoccurring in WMP comments.

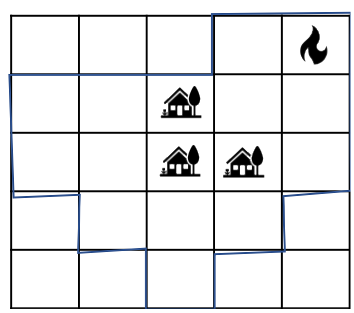
At the risk modeling working group meeting the utilities essentially noted that simulation uncertainty increases with longer simulation durations. This is expected, but it does not necessary answer whether longer duration simulations are needed or are useful. It may be prudent to require utilities to complete a study on how simulation duration and the number of simulations alters MAVF converted consequence values such as the skewness and spread of the resulting distribution, as well as the resulting risk scores and risk in proximity to WUI. For example, run a set number of simulations (n) each for a variety of durations (e.g. 8, 12, 24 hours) at a selection of locations with different conditions (e.g. weather, vegetation). In general, one would assume that longer fire spread simulations would increase consequence risk scores and potentially increase or alter consequence distributions both at a given asset as well as across a service area.

However, there remain many challenges to approximating real-world wildfires with simulations. For example, catastrophic wildfires can burn for many days before they are full contained and the impacts of suppression are not built into fire spread models. To our understanding, result validation is additionally challenging for longer simulations due in part to fire suppression efforts affecting actual wildfire fire-spread data. Based on these factors and the anticipated increase in uncertainty it is fair to question whether longer-duration, fire-spread simulations are the best way to evaluate granular ignition consequence risk.

We appreciate questions posed by Holly Wherman of CalAdvocates regarding the availability of other metrics, such as flame length, from the 8-hour simulations. While we are not experts in wildfire spread dynamics or modeling, we also wonder whether these other metrics, in addition to MAVF-derived consequence values, might improve granular consequence values based on the existing 8-hour simulations. For example, could alternative metrics such as flame length and spread rate also inform the potential for a given simulation outcome to further develop into a major wildfire? Could these simulated wildfire properties inform an estimated efficacy of suppression?

We also postulate that consequence values that do not take into account simulated fire properties such as spread rate and flame length may simply be missing important factors that determine ignition consequence past the 8-hour simulations. For example, suppose two simulated match-drop fires originating from the same location cover somewhat different areas but still pass-through locations with the same structures (Fig. 1). Both fires may have similar consequence scores based on the MAVF methods for valuing land, structures, and population (e.g. lives > structures > land). However, if the fire properties in the blue simulation are more aggressive (e.g. longer flame length and faster spread rate), the potential for this fire to cause substantial additional damage and become a catastrophic wildfire could be greater. A limiting factor for appropriately assessing wildfire consequence potential could be linked in part to consequences based solely on the MAVF versus taking into account wildfire properties.

Figure 2 Example of two simulated match-drop fires (red and blue) that may have similar consequence scores depending on the MAVF conversion functions, but might have different potential to become catastrophic fires due to their properties such as flame length.



GPI recommends that utilities: (1) Report on whether MAVF derived consequence scores from 8-hour wildfire spread simulations are able to adequately inform the 8+ hour destructive potential of each simulation based in variability in simulated fire properties, or if MAVF scoring is unintentionally narrowing or flattening the distribution of consequence risk at a given location; and (2) Work with CalFire and other fire spread and suppression experts to evaluate if and how other wildfire simulation output parameters can inform granular 8+ hour wildfire spread and consequence risk based on fire properties. The proposed match-drop simulation study above could compliment these assessments by informing how both fire properties and consequence values evolve over longer duration simulations, prior to implementing longer match-drop simulations across the entirely of California.

GPI also remains concerned about whether and how utilities are accounting for consequence associated with developed areas designated as "unburnable" in the wildfire simulation models. It may be reasonable to revisit wildfire simulation consequence scores in conjunction with planned wildfire suppression modeling discussions.

1.4 Ingress and egress risk evaluation methods may overlook important factors limiting evacuation rate.

Based on SCE's initial summary of methods we are concerned that using the metric of population density per road miles may overlook the importance of egress/ingress bottle neck points and the ratio of these bottle necks to population density and overall road miles. For example, the attendance to square foot ratio in a theater will not change whether there are 1 or 2 exits, however the evacuation rate will. Dense city centers may have a much higher population to roadway ratio compared to communities in the WUI. However, these cities may have many exits via highways and thoroughfares while small WUI communities constrained by parklands and terrain features (e.g. peaks and valley walls) may have very few egress/ingress pathways. For example, in one reported instance "Debris blocked a road that serves as a single exit for a community, and residents had to be helicoptered to safety (2017 Northern California Wildfires).[1]"

Utilities should provide a summary of how their methods take into account existing studies on wildfire evacuation, and how they are similar and different from existing methods. For example, the publication *Mapping wildfire evacuation vulnerability in the western US: the limits of infrastructure*, by Thomas J. Cova, David M. Theobald, John B. Norman III, and Laura K. Siebeneck.

Utilities should also discuss how their analyses and assessments take into account community evacuation plans within their territories. For example, with respect to community evacuation plans, one report cites that "officials implemented contraflow on the Pacific Coast Highway to increase capacity and ease congestion [during the 2018

Woolsey Fire].[1]" Evacuation plans such as these could be in place and feasible in some locations and not in others.

1.5 Flattened risk scores mask the overlap of risk from multiple risk drivers such as layered lower (e.g. CFO-animal) and higher (e.g. CFO-vegetation) frequency risk drivers. This removal of information presents challenges for assessing how modeling methods influence granular risk scores and inform risk mitigation.

By flattening risk scores from all drivers into a single risk value and risk map it is not possible to determine relationships (e.g. correlations) between different risk drivers. For example, whether planned mitigation locations are in fact substantially altered by CFO-animal caused wildfire risk or if these risks are coincident with locations characterized by high vegetation (e.g. forested lands) that would be targeted for mitigation due to CFO-vegetation ignition drivers. While not a technical aspect of the model methodology, the format in which the model outputs are presented can either facilitate or limit stakeholder evaluation of model changes and resultant outcomes as well as how the outcome is used to inform mitigations. We also raise the issue that ongoing developments to the wildfire risk models and the need for external review will likely extend beyond the scope of what can be accomplished during the Risk Modeling Working Group.

GPI advocates for improved transparency into risk modeling outputs, including access to layered interactive maps with model version control. These maps will help stakeholders and parties to the Risk Modeling Working Group evaluate the impacts of changes to modeling assumptions and inputs on granular risk scores, as well as the implications of these models for mitigation prioritization and approach.

1.6 Utilities are in the process of determining risk model uncertainty at the individual variable level, though progress at each utility is not transparent.

We focus our discussion on utility Machine Learning (ML) probability of ignition (PoI) or likelihood of risk event (LoRE) planning models. In terms of model assessment prioritization GPI is at this time generally less concerned with the development of

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[1] Review of California Wildfire Evacuations from 2017 to 2019 (2020), Wong, Stephen D., Broader, Jacquelyn C., Shaheen, Susan A., PhD

Technosylva fires spread models and operations models that include weather forecasting models. While this prioritization should not exempt these models and the model inputs/assumptions from review, we take into account factors such as uniform adoption of Technosylva and more mature weather forecasting models. This is in contrast to the newness and variability of ML PoI models and their influence on wildfire risk modeling for the purpose of mitigation planning.

GPI appreciates insight from the utilities during the July 13 meeting regarding progress on assessing model uncertainty. The utilities report that model uncertainty assessment is at the individual variable level and challenges to determining variable uncertainty include identifying the basis for validation, such as SME input, data, or data quality. It is not apparent how far along each utility is towards assessing covariate uncertainty in their ML PoI planning models, nor to what degree they are able to rank those variables from largest to least influential uncertainty on the model output as a whole. There is also likely substantial model sensitivity to factors such as specific covariate selection, covariate definitions, and other modelling assumptions. This assessment is based on the instability in PG&Es risk ranking model, informed by large changes to risk scores and ranks in their 2022 WMP Revision Notice Response. The stability of SCE's and SDG&E's PoI models is relatively unknown, although they have not specifically reported large shifts in their model-derived, circuit-risk rankings.

At this time stakeholders do not have a window into the specific covariates the utilities are employing in ML PoI planning models, nor the data sources and definitions for those covariates. For example, a covariate such as maximum wind speed at the time of an outage would minimally require selecting a dataset that was available at the time of the outage, a subset of the data from a location proximal to the outage (e.g. interpolated between weather stations or at a nearby weather station), and a specified window of time from which the max windspeed is selected. This single covariate includes a specific data set and multiple assumptions, each of which can introduce uncertainty and bias prior to even defining the algorithms that link the covariate to the training dataset to produce the output prediction. Insight into risk driver PoI covariates will help stakeholders assess high-level similarities and differences between the utility PoI planning models such as available data inputs, granularity, and quality (e.g. tree height, species, vegetation density, clearance, equipment age, condition, max versus average wind speed, etc.).

The 2022 WMPs provided tables of input data sets and sources of uncertainty. However, these tables did not inform how the data are interpreted to generate model covariates and the uncertainty lists and assessments were incomplete. GPI supports additional transparency into the utility ML PoI planning model covariates. Utilities should provide a list of covariates for each modeled risk driver including the underlying dataset and covariate definition (e.g. max wind speed is determined at +/- 1 hour from the time of an outage from the closest available weather station, which has 10 m data interval). This list should be updated for each new model version as needed. Utilities should also provide a summary of which covariates have the most predictive power, and which are anticipated to result in the most model uncertainty. Utilities should also provide a plan for how they will begin to address uncertainty at the covariate level.

2. Ideas and areas for future modeling improvements you think should be included in the risk model guidance document, including prioritization based on importance.

We suggest including the following areas relating to future modelling improvements in the risk model guidance document. These are roughly ranked based on prioritization and correspond to lessons learned in (1) above:

2.1. Establish a wildfire risk mitigation planning target, for example a 1-in-10-year wildfire risk event planning threshold, or other metric that can guide wildfire risk planning models.

2.2. Machine learning PoI planning models may result in biased outputs. An assessment of result bias is warranted to mitigate the potential for risk mitigation blind spots.

2.3. Evaluate existing and alternative consequence quantification approaches and/or whether longer fire spread simulations are necessary is an area of need.

2.4. Ingress and egress risk assessment methods should include a summary on how they leveraged existing evacuation rate and challenge assessments, how their methods are similar and different from these existing methods, how they validate and verify their models, and how they take into account community evacuation plans.

2.5. Provide recommendations on PoI, consequence, and total modeled risk result reporting format in order to facilitate the risk model and application external-review process. For example, reporting flattened risk scores mask the overlap of risk from multiple risk drivers such as lower (e.g. CFO-animal) and higher (e.g. CFO-vegetation) frequency risk drivers. GPI recommends providing access to the layered risk maps via a data portal to improve transparency and external review.

3. Possible topics you want to be covered in the second round of meetings (current tabled items include egress/ingress, smoke impacts, and suppression impacts)

GPI supports these currently tabled topics for the future round of meetings. We also recommend discussing the following topics:

3.1. Wildfire risk planning target. Is a planning target needed and if so, what form should or could a planning target take?

3.2. Risk modeling reporting standards. While this does not address the nuts and bolts of model development, reporting methods and results is foundational to the review process. This will guide recommendations to the OEIS regarding the types of risk modeling results and formats needed to appropriately review model updates and the influence of those updates on output predictions.

3.3. Ingress/egress. We look forward to additional discussion on how the utilities are modeling or accounting for risk associated with ingress and egress points.

3.4. SMJU risk models. While the SMJUs engage in the risk modeling meetings their wildfire risk planning models often do not compare with the IOU risk models in terms of method, scope, or maturity. Furthermore, the evaluation of SMJU wildfire risk modelling approaches is generally overshadowed by discussions focused on IOU modeling. A future meeting should focus on SMJU risk modeling methods for quantifying PoI and consequence risk components.

Components that raise concern are comments suggesting that ML PoI output predictions and consequence values are considered dependent. This appears to be at least partially due to the lack of ignition risk modeling for risk drivers such as CFO-animals, and other potentially non-weather-related outage and ignition causes. PacifiCorp also stated that they did not have a data scientist currently on their staff, suggesting risk modeling advancement may be paused.

The risk modeling working group should take care to not inadvertently overlook the SMJUs based on the perception of size. These smaller utilities still oversee substantial customer accounts in HFTD Tier 3 regions. PacifiCorp serves a large contiguous service area that spans from California and into Oregon. This large service area, as well as service areas in Utah, Washington, Idaho, and Wyoming, suggests PacifiCorp may have larger relevant datasets and staffing capabilities than just its California territory and customer-base might imply. The perception of fewer ignitions and utility wildfires in SMJU service areas in general is an artifact of relatively low frequency ignition rates and ever rarer wildfire occurrences integrated across smaller regions. Statistically speaking the SMJUs are just as prone to wildfire risk as the IOUs.

Respectfully Submitted,

Gregg Morris

Gregg Morris
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